An Optimal State Feedback Controller Based Neural Networks for Synchronous Generators

Moath H. Al-Qatamin
Electrical Engineering Department, King Khalid University, Saudi Arabia

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ABSTRACT

In this paper, an artificial neural network (ANN) is designed to optimize the matrix gain of state feedback controller. A linear mathematical model of a synchronous generator with excitation system is used as controlled system. The conventional methods that used to find the matrix gain need tedious calculations with compared to neural networks. The simulation proves that the proposed feedback controller based neural network optimization method has the better result in order to prove the dynamic performance of a single machine connected to infinite bus system(SMIB). The robustness of the proposed controller is tested by disturbance in excitation voltage. The results are compared with results of controller based on conventional methods. The potentials of the proposed technique are investigated using MATLAB software.

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Corresponding Author:

Moath H. Al-Qatamin
Department of Electrical Engineering,
King Khalid University, Saudi Arabia. P.O 394, Abha 61411
Email: malqtameen@kku.edu.sa

1. INTRODUCTION

There are hundreds of generating units in an interconnected power system. These units transmit the power to loads by long transmission lines. When a power system subjected to small and sudden disturbances, low frequency oscillations will be generated. If these oscillations are not well damped, they will grow in amplitude and limit the power transmission capability of the network [1]. Synchronous generator excitation control system (SGECS) is one of the most important measures to enhance power system stability and to guarantee the quality of electrical power it provides. An additional control signal in generator excitation system is usually used to improve the stability of the system. Some closed-loop feedback control theories can be used to generate control signal in excitation system.

In recent years, there is a trend that the new control theories are used in the SGECS with the development of the modern control and intelligent theories [2].Studies on state feedback controller of synchronous generators system have been reported well in the literature. Many attempts were made in last years regarding the design of state feedback controller for synchronous generators. In Ref [3], an adaptive design of an automatic voltage regulator (AVR) control scheme for synchronous generators was introduced in the presence of unknown variations of power system operating conditions; the AVR design is based on pole-assignment technique and the estimation is performed by kalman filter. The main difficulty in designing the controllers based pole-placement technique is the selection of closed-loop poles locations. The author in Ref [4] designed a digital Optimal AVR of synchronous generator using Linear Quadratic Regulator. In Ref [5], the authors designed the linear quadratic regulator (LQR) weighting matrices based on Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). For these techniques, all state variables of the system must be physically measurable. From a control point view; it is known that the dynamic stability enhancement depends on the type of the excitation controller that is used for the synchronous generation units. However, the design of these control devices is far from clarity due to the nonlinear and complex behavior exhibited by power system. Hence, two assumptions that simply the excitation control design are currently widely accepted, namely: Considering a single generator connected to an infinite bus (SMIB) system, is very useful in describing the dynamics of a multi-machine system. Although the actual dynamics of a synchronous generator is extremely complex, the dynamic model used for controller design purposed can be of low order, i.e: fourth order system has shown to be adequate from a control viewpoint [6]. In this paper, a simple Neural Network model is designed to generate the matrix gain ***K*** of state feedback controller by picking-up the steady state gains of proposed neuro-controller. To the best of author's knowledge, there has been no published research in designing the state feedback controllers by using the proposed technique. Therefore the obtained results form a real contribution in the area of state feedback controller design based neural networks .The simulation results of the system under study are compared with the results that based on state feedback controller which generated by conventional optimal theory.

2. MATHEMATICAL MODELLING

A single- machine infinite bus (SMIB) power system as shown in figure.1 is used as study model in this paper. This model is consisted of a single synchronous generator connected through a transmission line to a very large network approximated by an infinite bus. The fourth order nonlinear dynamical model of the SMIB power system is presented by differential equations [7]:

$$\dot{\omega} = (1/M)(T_m - T_e - D\omega) \tag{1}$$

$$\dot{\delta} = \omega_b \omega \tag{2}$$

$$\dot{e}_q' = \frac{1}{T'_{do}}[E_{FD} - e_q' - (x_d - x_d')i_d] \tag{3}$$

$$\dot{E}_{FD} = \frac{1}{T_A}[K_A(v_{ref} - v_t + u_{pss}) - E_{FD}] \tag{4}$$

By linearizing the above equations on at operating point, we have the state variable model of a single machine to infinite bus as:

$$\begin{aligned} \dot{X} &= AX + BU \\ Y &= CX \end{aligned} \tag{5}$$

Where state variable X is defined by: $X = [\Delta\omega, \Delta\delta, \Delta e_q', \Delta E_{FD}]$ where: $\Delta\omega$:Speed Deviation; $\Delta\delta$:Load Angle Deviation; $\Delta e_q'$:Voltage due to Flux Linkage Deviation; ΔE_{FD}:Field Voltage Deviation. In the above system matrix A and B are represented by:

$$A = \begin{bmatrix} \frac{-D}{M} & \frac{-K_1}{M} & \frac{-K_2}{M} & 0 \\ \omega_b & 0 & 0 & 0 \\ 0 & \frac{-K_4}{T'_{do}} & \frac{-1}{K_3 T'_{do}} & \frac{1}{T'_{do}} \\ 0 & \frac{-K_A K_5}{T_A} & \frac{-K_A K_6}{T_A} & \frac{-1}{T_A} \end{bmatrix} B = \begin{bmatrix} 0 & \frac{1}{M} \\ 0 & 0 \\ 0 & 0 \\ \frac{K_A}{T_A} & 0 \end{bmatrix} \quad U = [\Delta U_{ex}; \Delta T_m]$$

Also; the terminal voltage deviation and output power deviation can be expressed respectively as:

$$\Delta V_t = K_5 \Delta\delta + K_6 \Delta e_q' \; ; \; \Delta P_o = K_1 \Delta\delta + K_2 \Delta e_q' \tag{6}$$

Where the system parameters are defined and listed in Table 1.
The input mechanical torque ***Tm*** is treated as a constant in excitation controller design [8].

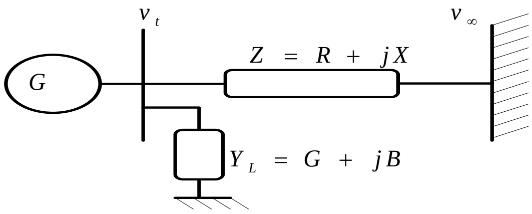

Figure 1. System model

3. CONTROLLER DESIGN

3.1. Optimal Control

For the linear optimal control design of an electric power system, a quadratic performance index is usually chosen as:

$$J = \frac{1}{2}\int_0^\infty [x^T Qx + u^T Ru]\,dt \tag{7}$$

Where: Q and R are the weighting matrices (or penalty matrices) of the state and control effort, respectively. To optimal control design the Eq.(7) must be minimum. The major step of the minimization is to append Eq.(5) to Eq. (7) to form a Hamiltonian generalized-energy function as shown in Eq.(8):

$$H = \frac{1}{2}[x^T Qx + u^T Ru] + p^T [Ax + Bu] \tag{8}$$

Where p is called the co-state vector and can be calculated from the Riccati equation [9]. To find the gain matrix ***K*** of state feedback controller based linear optimal control, the following condition must be satisfied:

$$\frac{\partial H}{\partial u} = 0 \tag{9}$$

Carrying out the differentiation of Eq. (8), the result is shown as:

$$Ru + B^T p = 0 \tag{10}$$

And the control law will be given by:

$$u = -R^{-1}B^T p \text{ or } u = -Kx \tag{11}$$

The resultant closed-loop system is then:

$$\dot{x} = (A - BK)x \tag{12}$$

In this work, the values of the Q and R matrices that used in the simulations are chosen to give acceptable performance of closed-loop system and to minimize the control effort as:

$$R = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \qquad Q = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The matrix Q is chosen as identity because the system states have equally important. Therefore, the gain matrix ***K*** of control law ***u=-Kx*** is:

$$K = \begin{bmatrix} -0.7140 & 0.0523 & 0.3027 & 3.1424 \\ 131.5526 & 2.4774 & -1.9172 & -0.0001 \end{bmatrix}$$

The resulting controller ***u*** is known as linear- quadrant state feedback regulator [10]. From this state feedback controller, we can easily notice that all state variables of the system must be physically measurable.

3.2. Neural Network Control

Neural networks offer an excellent approach for computing inspired by the brain's behavior. The elements (neurons models) are thought to mimic the basic behavior of real human neurons. Different forms of inter-connection of neurons will produce different neural network strategies such as feed forward and recurrent networks. The strength of the neural networks approach is its ability to generalize from the training examples to the entire domain and its ability to accommodate noise and poor data. One of the most popular architectures for ANN control is the multilayered neural network (MNN) trained with the back-propagation (BP) algorithm. The back propagation algorithm is used to update the weights of multilayer perceptron network algorithm. According to the delta rule, the weights are updated as follows:

$$\Delta w_{ji}(k+1) = (1-mom)\times\eta\,\delta_i o_j + mom\times\Delta w_{ji}(k) \tag{13}$$

Where j is the previous neuron index, *i* is the present neuron index, *k* is the iteration number, w_{ij} is the weight from neuron *j* to neuron *i* , η and *mom* are the learning and momentum coefficients respectively[11]. In this work, the ANN chosen is of a feed forward type, using back-propagation algorithm for weight updating. This multilayered network has five inputs. The system states and excitation signal is used as input to proposed NN. The proposed NN has two hidden layer with 10 neurons for each layer. The nonlinear transfer function of the nodes is chosen to be a sigmoid function. Since it is the most proper activation function to perform linear and non-linear functions modeling, control and classification. The training parameters in the back-propagation algorithm, i.e. the learning factor and the momentum coefficient were selected as 0.6 and 0.9 respectively. The training process is shown in figure 2, where the desired controller (u_d) is the target data that obtained from optimal controller law in previous section. The training process will be stopped when the prespecified error or the maximum epoch are reached. After the training of NN controller is completed and tested, the optimal gain set is chosen according to the results shown in figure (3), which shows the performance of neuro-controller. The graph indicates that the best steady- state gains of controller output are $k_1= 45.7010$, $k_2=11.5321$.

From these results, the gain matrix ***K*** of the proposed state feedback controller based neural network can be written as:

$$K = \begin{bmatrix} 11.5321 & 0 & 0 & 45.7010 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

In this proposed state feedback controller based neural network only two state variables of the system must be physically measurable. By comparing the proposed matrix gain with one which generated by conventional control method, we can easily notice that only two state variables must be known to generate the desired control signal.

4. RESULTS AND DISCUSSION

The Runge-Kutta numerical method is used to simulate the power system under study by using MATLAB software. The system parameters and initial conditions which used in simulation are taken from Ref.[7] and listed in Table 1. The performance of the proposed state feedback controller based neural network is tested in two cases:

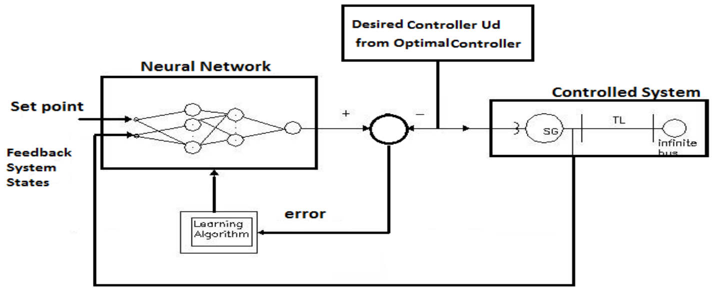

Figure 2. Structure of the direct inverse modeling in the NN training

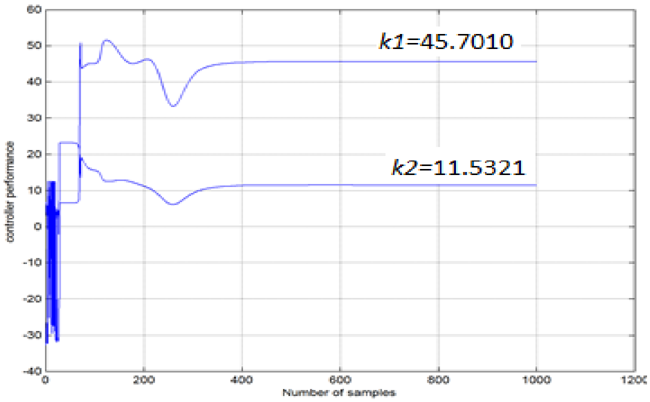

Figure 3. Performance of the Neural Controller

Table 1. Initial Conditions and Nominal System Parameters

Parameter	Description	Value	Unit
Po	Initial Active Power	0.9	pu
Q0	Initial Reactive Power	0.3	pu
Vto	Initial Terminal Voltage	1.0	pu
H=M/2	Inertia Constant	4.64	Seconds
D	Damping Factor	0	pu
T'_{do}	Field Time Constant	7.76	Seconds
x_d	Direct axis Reactance	0.973	pu
x'_d	Direct Transient Reactance	0.19	pu
x_q	Quadrature axis Reactance	0.55	pu
TA	Exciter Time Constant	0.05	Seconds
KA	Exciter Gain	50	--
Re	Transmission Line Resistance	-0.034	pu
Xe	Transmission Line Reactance	0.8	pu
B	Local Load susceptance	0.262	pu
G	Local Load conductance	0.249	Pu
K1	Synchronous Machine factor	0.7901	--
K2	=	1.3459	--
K3	=	0.6033	--
K4	=	0.8905	--
K5	=	-0.0613	--
K6	=	0.7457	--

Case1: Nominal Operation.

The first simulation test concerns on the dynamic performance of the system under nominal conditions, i.e, no parameter changes and no disturbances. As depicted in Figure (4), the responses of the system exhibit a good transient performance. The comparison between proposed state feedback controller and optimal controller shows the effectiveness of proposed one in terms of overshoot and settling time.

Case2: 30% Step change in excitation voltage at different values of Exciter gain KA:
1. Exciter gain KA=50 (Nominal Value).
2. Exciter gain KA=20.

In order to test the effectiveness of the proposed controller, the 30% step change in excitation voltage is applied for 5 seconds at 15 seconds.

From Figure (5) and Figure (6), the better performance of the proposed controller over conventional one in damping out the step disturbance is explicit.

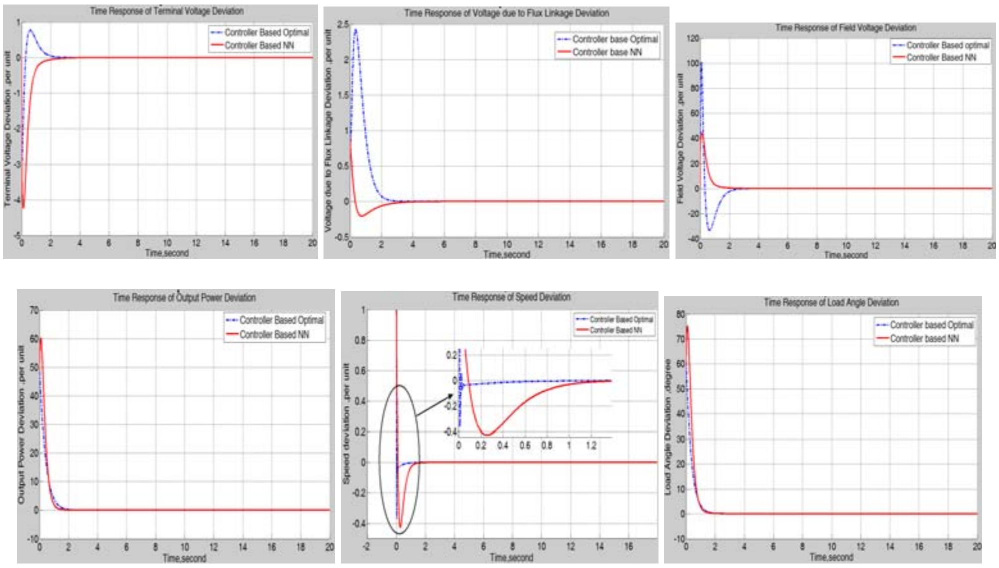

Figure4. Time Responses of the System under Nominal Conditions.

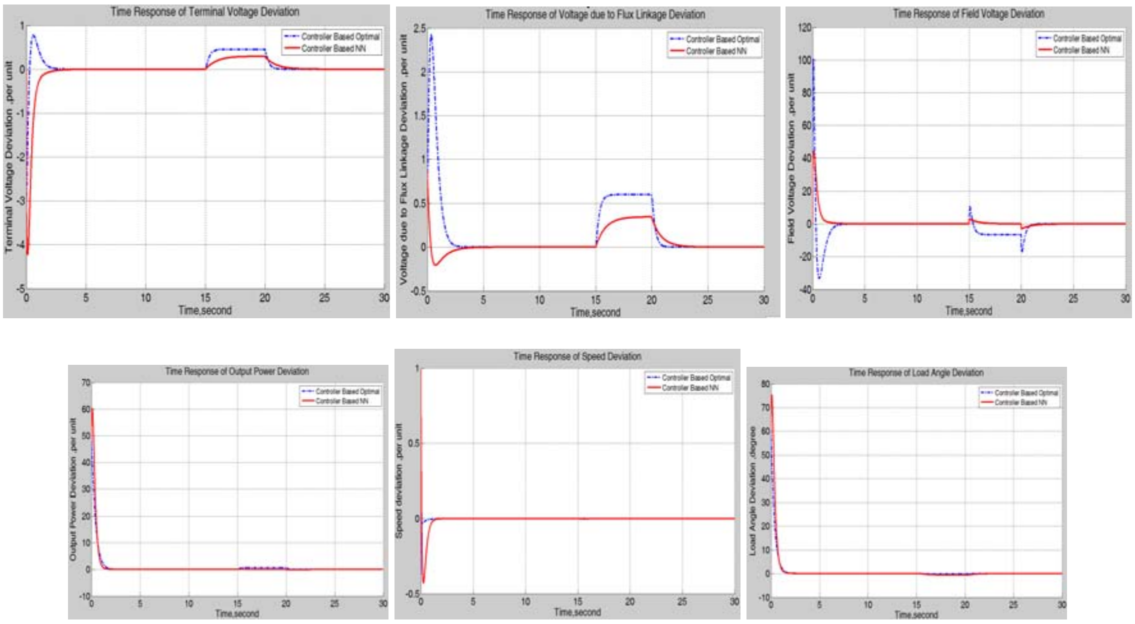

Figure 5. Time Responses of the System at 30% disturbance in Excitation Voltage with KA=50.

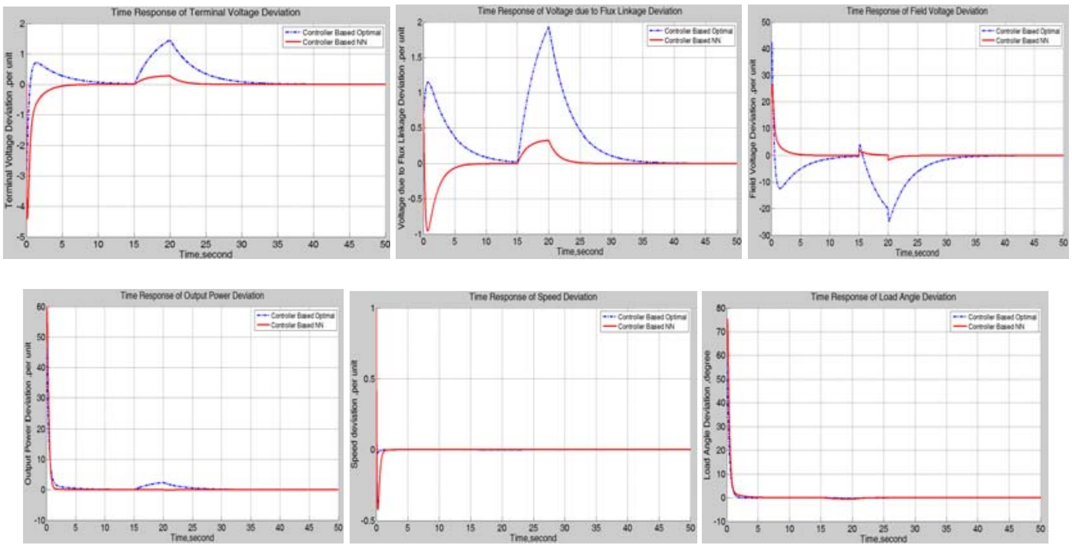

Figure 6. Time Responses of the System at 30% disturbance in Excitation Voltage with KA=20.

5. CONCLUSION

Multilayered neural networks have been successfully used to produce gain matrix ***K*** for the state feedback controller. A control signal based neural network is used to improve the dynamic performance of synchronous generator connected to infinite bus through transmission lines (SMIB). The simulation results with two test cases demonstrate the effectiveness of using the state feedback controller based neural network instead of conventional one. The proposed control strategy is suitable for real time implementation, because only two state variables of the system must be physically measurable to generate proposed control law. In contrast, the conventional control needs all state variables.

REFERENCES

[1] Prasertwong K, Mithulananthan N. Conventional and Fuzzy logic controllers at generator location for low frequency oscillation damping. *International Journal of Electrical Power and Energy Systems Engineering.* 2009; 2(3): 135-143.
[2] Gowrishankar K, Masud M. *MATLAB Simulink Model of Fuzzy Logic Controller with PSS and its Performance Analysis*, IEEE-International Conference On Advances In Engineering, Science And Management. March 30, 31, 2012.
[3] Fusc G, Russo M. A adaptive Voltage Regulator Design for Synchronous Generator, *IEEE Trans. On Energy Conversion.*2008; 23(3): 946-956.
[4] Ibraheem K. A Digital – Based Optimal AVR Design of Synchronous Generator Exciter Using LQR Technique, *Al-Khwarizmi Engineering Journal.*2011; 7(1): 82-94.
[5] Ghoreishi S, Nekouri M, Basiri S. Optimal Design of LQR Weighting Matrices based Intelligent Optimization Methods. International Journal of Intelligent Information Processing. 2011; 2(1):1-5.
[6] Maya P, Perez G. *Observer-based IDA Control of Synchronous Generators*. IEEE Trans. Conference on Decision and Control, USA December 2003.
[7] Machowaski J, Bialek J, Bumby J. Power System Dynamics Stability and Control. *Wiley*, 2012.
[8] Alireza SED AGHATI. A PI Controller Based on Gain-Scheduling for Synchronous Generator. *Turk J Elec Engin.* 2006; 14(2): 241-251.
[9] Lewis L. Optimal Control. *John Wiley & Sons*; 1986.
[10] Grzesiak, Ufnalski. *Neural- Network-based Programmable State Feedback Controller for Induction Motor Drive*. International Joint Conference on Neural Networks of IEEE, Vancouver Canada, July 16-21, 2006.
[11] Principe C, Euliano R, Lefebvre W. Neural and Adaptive Systems, *Wiley*, 2000.